

Beyond the Zero-Sum Debate: Designing for Agency and Efficiency in the Age of GenAI

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Abstract

As generative artificial intelligence (GenAI) becomes increasingly integrated into computer-supported collaborative learning (CSCL), educational technology faces a critical transition. Rather than treating instructional scripting and learner agency as a zero-sum debate, this paper explores how GenAI can serve as a dynamic intervention to balance efficiency and exploratory knowledge construction. Drawing upon seminal CSCL literature and the "Construction Paradox," where bypassing the struggle of creation inadvertently undermines deep cognitive understanding, we present a practical framework for AI-supported collaborative learning. By distinguishing between focal and supporting learning outcomes, educators and system designers can strategically determine when to offload process complexity to GenAI and when to preserve human inquiry, social interaction, and productive struggle. Ultimately, this framework ensures that GenAI enhances human agency and collective sensemaking without compromising the core values of collaborative learning.

Overview

In this IJCSCL twentieth anniversary article, we revisit historical computer-supported collaborative learning (CSCL) research and technologies in the context of the rapid evolution and use of generative artificial intelligence (GenAI). CSCL theorists and practitioners have long debated how technology should support learner development and what counts as evidence of that development. Some early CSCL research and technologies emphasized increasing agency by allowing students to take ownership of their learning, focus on inquiry-guided projects, and explore, collaborate, and build knowledge with a community of learners to develop higher-order skills and a deeper understanding of knowledge-building processes (Damşa & Ludvigsen, 2011; Cole & the Distributed Literacy Consortium, 2006; Scardamalia & Bereiter, 2006; Stahl, 2004, 2006). This orientation reflected a broader shift in CSCL toward understanding cognition as distributed across people, tools, representations, and interaction rather than residing solely within individuals (Suthers, 2006; Stahl, 2015). At the same time, other lines of research focused on the risks associated with leaving complex learning processes insufficiently structured, arguing for more explicit guidance to reduce the demands of collaborative interaction and domain-specific reasoning and to support more reliable, focused, and efficient learning of domain content (Kirschner et al., 2006; Rummel & Spada, 2005).

Rather than representing wholly opposing positions, these traditions reflect a longstanding design tension in CSCL around how much structure to provide, where to provide it, and which aspects of learning should remain under learner control. GenAI makes this tension more consequential because it can provide increasingly sophisticated forms of support while also making it easier to bypass processes that may themselves be necessary for learning. On the positive side, GenAI could make informational and strategic support more accessible across broader socioeconomic contexts. But if used in uninformed ways, it could also oversimplify educational activities, reduce learner agency, and circumvent opportunities for productive struggle and collaborative knowledge construction. Agency and efficiency, therefore, are not a zero-sum game; they are pedagogical choices with trade-offs. There is a time for

streamlining processes to optimize immediate performance and a time for preserving space for exploration, productive struggle, and collaborative improvisation through guided instruction (Hmelo-Silver et al., 2007; Kapur, 2008; Bransford et al., 2000).

One way CSCL has historically negotiated this tension is through instructional scripting: structuring how learning progresses and how technology guides or constrains activity. This work has produced important insights about activity design through macro scripts and interaction and information design through micro scripts, as well as their impacts on collective sensemaking (Vogel et al., 2017). How and when learners engage in collective sensemaking matters (Suthers, 2006), because it can mean the difference between meaningful knowledge construction and superficial coordination or division of labor among group members (Wecker & Fischer, 2011). The same may be true of how learners use GenAI to make sense of ideas and tasks. Groups can improve the quality of collective sensemaking over time through structured reflection aimed at improving their processes (Borge et al., 2018; Järvelä & Hadwin, 2013), and preliminary case studies suggest that GenAI can support learners in carrying out such reflection productively (Borge et al., 2024).

One purpose of an anniversary issue should be to take stock of what the field has learned and make that knowledge useful beyond the academic community. We aim to do so in keeping with Järvelä and Rosé's (2023) call to move forward without losing CSCL's foundational commitments. To this end, our paper builds on seminal CSCL scholarship, our current work, and human-computer interaction (HCI) methods for designing activity, information, and interaction (Rosson & Carroll, 2002). We synthesize this work to articulate underlying questions that we need to ask when designing GenAI-supported collaborative learning spaces. In doing so, we address what we call the Construction Paradox in GenAI use (Author et al., in press) and distinguish between focal and supporting learning processes to help determine when to move slowly and when to streamline supporting processes (Authors, 2019). Clarifying this distinction can help teachers and designers orchestrate activities that lead to desired learning outcomes while preserving the human judgment and improvisational richness that make collaborative learning cognitively and emotionally rewarding (Chi & Wylie, 2014; Sawyer, 2006).

To be clear, we are not advocating for adopting or integrating GenAI for learners at all costs. We believe society must resolve many economic, ecological, structural, and cultural issues before GenAI can be seen as a net positive and ethical resource for humanity. Technologies have always co-evolved with cultural and educational practices, and new technologies commonly generate both enthusiasm and fear (Collins & Halverson, 2009). GenAI, however, deserves particular attention because its rapidly developing capabilities carry substantial potential for harm if left unchecked (Bengio et al., 2025, 2026). Bengio et al. (2026) argue that a pathway to safe advanced AI requires experts to identify risks and provide guidance. Our position is pragmatic: people are already using these technologies. Researchers and technology developers therefore have a responsibility to help users understand potential risks, possible harms, and strategies for mitigating those harms so that, if they choose to use GenAI, they can do so more knowingly and responsibly. Within our area of expertise, we contribute to that effort by identifying risks GenAI poses to how people learn, think, and interact with others.

The Construction Paradox and Structured Support

A central problem in education is that we have largely confounded products of learning with learning itself. Learning is not directly visible, so educators infer learning through observable process behavior and artifacts such as essays, tests, projects, explanations, and other products. Because products are easier to assess than process behaviors, they have largely come to represent concept understanding and procedural competence, when in fact, they may not represent actual learning at all. For example, memorizing an essay outline or template (e.g., placing specific vocabulary words into a five-paragraph structure, using canned transition phrases, and inserting pre-selected quotes) to pass an exam does not mean a student actually learned the underlying reasoning behind the template or the higher-order skills necessary to write critically. A formulaic essay, the observable artifact, can look polished, coherent, and sophisticated without, say, knowing how to analyze an unfamiliar text, construct an original argument, write a coherent thesis, or adapt their writing for different audiences.

Generative AI has exacerbated and highlighted the problem by giving learners instant access to sophisticated completed products without the difficult cognitive work required to create them. Thinking deeply and learning new things is hard and time-consuming work. Generative AI tempts us to circumvent the cognitive effort needed to create artifacts we can use to generate new knowledge or share existing knowledge. In creating these products or using GenAI to explain concepts or complete assignments, learners may feel confident that they are learning, and instructors may see finished products and assume the same. However, when learners face related but novel problems that push them to apply knowledge, the illusion of learning becomes apparent.

This illusion of learning is what we call the Construction Paradox: learners may want to bypass full cognitive construction to move more quickly toward using knowledge, but their ability to meaningfully use and extend that knowledge depends on the construction they bypassed. Cognitive construction often depends on exploration, productive errors, strategic reasoning, and even frustration to develop more detailed internal models of the subject or phenomena people are learning. Cognitive construction is not merely an inconvenient step toward a product; in many cases, it is the learning itself.

Given the risks of circumventing knowledge construction, one could argue that learners should never use GenAI. However, the history of learning sciences and CSCL is strongly influenced by Vygotskian sociocultural theory, which argues that learning is an inherently social process in which cognitive development is driven by cultural context, language, tools, and interaction with others (Vygotsky, 1978). Many examples show that technological or instructional support, such as scaffolding, enables learners to participate in activities before they are developmentally able to perform every aspect independently (White & Frederiksen, 1998; Reiser, 2004; Quintana et al., 2004).

Kirschner and colleagues (2006) and others (e.g., Klahr & Nigam, 2004) argue that direct instruction excels when cognitive load is high, foundational conventions must be learned, or critical underlying knowledge is at risk. For example, teaching standard long division, chemical symbols, or matrix multiplication steps can prevent unnecessary frustration and incorrect steps. However, some concepts

and procedures, such as controlling variables in an experiment (Dean & Kuhn, 2007), can be learned over an extended period that allows for discovery and productive failure (Kapur & Bielaczyc, 2012), and the development of competencies for collective sense-making (Borge et al., 2018; Author, 2023).

Learning support or scaffolding with or without technology is not the problem. To use technology effectively as added support or direct instruction, we need to determine which parts of a learning task can be made easier, scaffolded, or offloaded, and which parts must remain with learners because struggling with, reasoning through, and constructing those aspects is necessary for the desired learning outcomes. The best instructional approach provides learner agency to explore and make mistakes, combined with direct instruction triggered when learners identify problems or get stuck (White & Frederiksen, 1998; Authors, 2016). This just-in-time support provides a middle ground between learner agency and efficiency, allowing learners to guide learning paths and use technology as informational and strategic escape hatches when they get stuck.

For example, as part of previous work, we designed a computer-supported environment XXXXX for learning and doing science inquiry projects as an intervention designed to help learners improve metacognitive skills and their understanding of the practice of scientific knowledge building (Authors, 2002; Authors, 1998). XXXXX incorporated software advisors that provided general advice on critical parts of the inquiry cycle, such as questioning, hypothesizing, analyzing, and modeling. By giving general advice rather than step-by-step procedures, the system helped students conduct more epistemologically authentic experiments. Students using XXXXX could also select the type and timing of advice from advisors. This framework gave students greater agency and facilitated higher-level goal orientations (such as mastery or knowledge building rather than task completion), which in turn produced higher levels of competence (Author et al., 2002). Ultimately, findings on this type of middle-ground interactional support showed that it developed both scientific domain knowledge and higher-order reasoning skills (Author et al., 2013).

GenAI use as a learning intervention

The SCI-WISE example illustrates that the central design problem is not whether technology should support learning, but where support should be placed. Ideally, support should increase learners' capacity to accomplish a specified task without eliminating the cognitive construction needed to develop the underlying skills and reasoning required to maintain that capacity without technological support. Historically, decisions related to technology support in CSCL largely occurred before each round of technology deployment. Researchers had to decide on instructional support scripts in advance, i.e., which processes to support, how to sequence activities, which roles learners should assume, and what prompts or scaffolds to provide to encourage productive interaction (Dillenbourg, 2002; Weinberger et al., 2005; Kollar et al., 2006; Fischer et al., 2013; Vogel et al., 2017). Early scripting work made explicit that these design choices could structure both the epistemic work learners were expected to carry out and the social processes through which they interacted, while also raising concerns that too much scripting could constrain the very collaborative activity designers hoped to support (Dillenbourg, 2002;

Rummel, et al., 2009, Weinberger et al., 2005). This concern matters because collaborative learning develops through multiple layers of productive interaction in which learners negotiate ideas and jointly construct knowledge objects (Damşa, 2014; van Aalst, 2009). Although later work introduced more flexible and adaptive forms of scripting (Dillenbourg & Tchounikine, 2007; Adamson et al., 2014), these adaptations still generally occurred within a design space whose components and contingencies had been specified in advance. Designers therefore had to anticipate the kinds of support learners might need and build those possibilities into relatively fixed support structures prior to each deployment.

Jeong and Hmelo-Silver (2016) cautioned that technological supports for collaboration must be carefully calibrated to facilitate productive interaction without interfering with longer-term learning goals. This concern reflects a longstanding tension in CSCL between providing enough structure to promote productive knowledge construction and preserving sufficient learner responsibility and flexibility for genuine collaboration to emerge (Dillenbourg, 2002; Kollar et al., 2006). Although CSCL designers could structure activity through scripts, roles, prompts, and other programmed supports, these supports still required designers to make difficult judgments about how much guidance to provide and where to preserve learner responsibility. The integration of Generative AI (GenAI), systems capable of synthesizing text, imagery, code, and audio by extracting patterns from vast datasets, fundamentally disrupts this structured paradigm and raises the stakes when there is a lack of forethought about the inherent trade-offs in educational design choices (Collins, 1996).

Generative AI offers new possibilities for interactional support that, while similar to previous AI models, cannot be assumed to produce similar outcomes due to the scale and type of data used to create predictive models. LLM-enabled systems can interpret more features of an unfolding activity and generate support in response to what learners are doing moment to moment, with far more diverse potential interaction paths than previous intelligent tutoring systems. Support can now be generated, altered, or withheld in response to an unfolding interaction. Support can vary in timing, form, and intensity depending on whether learners need to elaborate an idea, provide evidence, consider another perspective, reconcile competing claims, or reflect on the quality of their reasoning, promoting more sophisticated sensemaking between the human and the agent.

This flexibility creates new opportunities for balancing learner agency and efficiency, but it also makes the Construction Paradox more consequential. If GenAI can perform increasingly sophisticated portions of a task on demand, then deciding what to support, what to offload, and what must remain part of learners' own sensemaking becomes an ongoing pedagogical decision rather than a feature of the original instructional design. In many ways, the LLMs provide greater access to discovery learning, but without the informed guidance we argue is necessary (cf. Kolodner et al., 2003).

GenAI outputs vary widely and are highly sensitive to prompt inputs, making the trajectory and outcome of human-technology interaction largely unpredictable and uncontrolled. Rather than a static communication channel or tool, GenAI functions as a dynamic, simulated conversational agent within group interactions, extending a longstanding CSCL concern about how technological affordances are

appropriated and given meaning through collaborative interaction (Dwyer & Suthers, 2006). This introduces emergent, non-linear discourse and resource pathways where the AI might generate unexpected counterarguments, offer creative synthesis, or introduce faulty information or resources that challenge group consensus. Consequently, the shift from predictable, pre-scripted CSCL architectures to generative, emergent environments forces a fundamental shift in pedagogical design: educators and researchers must pivot from rigid task pre-structuring to supporting real-time adaptive regulation, critical prompt orchestration, and continuous peer evaluation of AI-generated content. If the aim of using GenAI is to enhance learning, its use can be framed as a learning intervention: the deliberate design of a learning activity, including the information provided and the instructional interactions provided by the system or expected of the students.

Palincsar and Brown's (1984) seminal work on reciprocal teaching provides a foundation for thinking about the types of knowledge needed to inform intervention design. They argue that intervention design requires developing theories to guide design decisions. In previous work developing a system called XXXX we translated their guidance into conceptual models to guide activity, information, and interaction design in a technological system: a model of the task, a model of collaborative competence, a model of assessment, and a conceptual model of the regulation process (Authors, 2019). However, when we published this design narrative about the XXXX system, we did not specify how these models helped us decide how to use technology to support learning. So, we do so now.

When using these models, we first decided what skills and competencies the task required and what conditions were necessary to support the task, i.e., what information and experiences were needed to help learners construct knowledge to build skills and competencies. Then we asked what knowledge needed to be constructed deeply, i.e., where did learners need the most agency to explore and make mistakes so these experiences could serve as building blocks for more complex thinking later. The aim of our XXXX system was to develop learner competence when collaborating: the ability to regulate their own learning activity over time to engage in more sophisticated collaborative activity. So, we asked what observable process indicators could serve as markers of collaborative competence and how we could make these visible to learners. Finally, because regulation is difficult, we asked how we should support productive reflection to move from less to more ideal process indicators: should we script it, and if so, how and to what extent (Authors, 2018, 2022)?

When translating this approach to GenAI use specifically, we can ask which conditions need to be cultivated for specific tasks; which cognitive and social processes must remain part of learner construction; and which supporting processes can be more closely controlled, directly taught, or offloaded. And finally, what should learners reflect on and evaluate to become increasingly capable of regulating future-oriented activity, including the use of GenAI? Based on the current sophistication of GenAI, the key implications for CSCL are:

- **From Fixed Scripts to Adaptive Regulation:** Groups must now dynamically monitor, critique, and verify team members' and GenAI contributions rather than simply following fixed sequence scripts.

- **GenAI as an Emergent and Adaptive Resource:** The non-deterministic nature of GenAI makes it an active, unpredictable resource in shared meaning-making rather than a neutral backdrop that simulates human social interaction.
- **Reframing Evaluative Scaffolding:** Pedagogical goals must emphasize guiding students through iterative cycles of prompt engineering, critical discourse, and error detection of both learning content and technologically supported sense-making processes.

Our approach to designing technological interventions can be adapted for use with GenAI. Before deciding what GenAI should do, we must understand what learners are expected to learn and what constitutes competent performance. Asking these questions allows designers to distinguish between focal learning processes/outcomes and supporting task demands. Some activities may be necessary to complete a task but are not what the learner needs to develop. Other activities are central because engaging in them is precisely how the learner develops the focal competence. That distinction becomes critical when deciding what to support or offload to GenAI.

Distinguishing between focal and supporting learning outcomes

Järvelä and Hadwin (2013) argue that successful group problem-solving requires groups to jointly regulate their collective cognitive, metacognitive, and socio-emotional processes. This relational perspective informs instructional design: shared regulation can *support* mastery of complex course content or serve as the *focal learning outcome* when teaching students to collaborate effectively. Similarly, Janssen et al. (2010) analyze the dual cognitive demands placed on collaborative teams: handling the domain-specific task while simultaneously managing group interaction and coordination. If the primary goal is the learning of domain content, then without explicit scaffolding for group management, the cognitive load from secondary interactional and coordination processes can hinder primary task performance (Janssen et al., 2010). This provides strong empirical justification for relational task design and targeted process support in CSCL environments.

In our previous work designing the XXXX system, we deprioritized domain content learning to make higher-order collective thinking processes a first-order learning outcome (Authors, 2019). We designed the CREATE system to help teams learn how to improve collaborative processes through collective regulation of sense-making activity, hypothesizing that doing so would eventually lead to more sophisticated domain content talk. Thus, higher-order collective thinking processes were the primary learning task, and socio-metacognitive skills and domain content were the secondary learning tasks. Here, we extend this distinction by referring to focal and supporting learning outcomes and processes.

The distinction between focal and supporting learning outcomes is relational: what counts as focal depends on the competence an intervention is intended to develop. Specifically, in CREATE, the focal aim was to develop collaborative competence: learners needed to understand collective sensemaking processes and become increasingly capable of improving those processes over time. Regulation was treated as a supporting meta-task because monitoring and regulating collaborative activity were

necessary to improve performance on the focal task. Learners therefore needed opportunities to compare existing collaborative activity with models of desired activity, identify problems, consider strategies for improvement, apply those strategies during future collaboration, and repeat this cycle over time.

This distinction, combined with user studies (Authors, 2015; Authors, 2018), influenced what we chose to structure and what we deliberately left under learner control. Because collaboration was the focal activity, XXXX did not interrupt or tightly script the collaborative discourse itself. Learners needed opportunities to experience the complexity of collaboration, make decisions, encounter problems, and try to manage them themselves. In contrast, the system more strongly orchestrated and scripted the regulatory activity that followed collaboration. It structured when reflection occurred, directed learners' attention to theoretically grounded dimensions of collaborative competence, constrained what they could reflect on, and provided models and strategies to support improvement.

Importantly, however, supporting a regulatory task did not mean performing the regulation for learners. XXXX provided models of competence, assessment criteria, and possible strategies, but learners still had to compare those models against their own activity, decide what they had done well or poorly, identify areas for improvement, and determine which strategies they would try next (Authors, 2022). In this way, technology reduced some of the informational and procedural burden surrounding regulation while preserving the judgments through which learners could develop greater competence and agency.

This example illustrates why the distinction between focal and supporting processes is useful for thinking about GenAI. If a process is central to the competence we want learners to develop, then learners need meaningful opportunities to engage in that process themselves. Other aspects of the activity may be candidates for greater technological support when that support allows learners to devote more attention to the focal construction. However, supportive processes should not automatically be treated as expendable or fully off-loadable. A supporting activity may contain judgments or strategies that learners also need to develop.

No type of knowledge or activity is inherently focal or supporting. What is focal and what is supporting shifts depending on the desired learning outcome at that point in time (Table 1). For example, regulation supported the development of collaborative competence in XXXX, but it could itself become the focal outcome in an intervention specifically designed to develop metacognitive or socio-metacognitive expertise. Similarly, domain knowledge, heuristic strategies, control strategies, or learning strategies may move between focal and supporting roles depending on the intended learning outcome. The critical design question is therefore not simply what can technology do, but what must learners do themselves to develop the competences we are trying to cultivate?

Table 1
Key Characteristics: Focal vs. Supporting Tasks

Dimension	Focal (Primary) Tasks	Supporting (Secondary) Tasks
Core Definition	The central target competence or learning outcome the intervention aims to build.	The underlying mechanism, coordination process, or meta-task needed to reach the focal goal.
Instructional Control	Unscripted & Open: Kept under learner control to preserve authentic friction, decision-making, and problem-solving.	Structured & Orchestrated: Strongly scaffolded or scripted by software/technology to minimize procedural overhead.
Technological & GenAI Role	Preserved for Learners: Learners must execute these activities directly to construct expertise and agency.	Targeted Scaffolding: Technology reduces informational complexity, formats data, or provides regulatory prompts but still preserves higher-order decision-making.
Cognitive Load Strategy	Receives the majority of the learner's active cognitive bandwidth and deep effort.	Cognitive load is minimized or organized to prevent it from hindering main task performance.

Ultimately, effective instructional design depends on a clear understanding of the focal and secondary learning tasks for a given case. Recognizing that what serves as background scaffolding in one context may become the core learning target in another. Failing to account for these relational dynamics risks offloading the very cognitive and reflective judgments learners need to build agency and expertise. By intentionally structuring secondary activities while preserving learner autonomy over focal processes, designers can create or use educational technologies, including GenAI, to alleviate cognitive strain without stripping away the essential friction necessary for meaningful learning.

Cultivating the social conditions for learning

Deciding what learners must construct is only part of the design problem. Learning does not occur through interaction with a task or technological system alone. Cognitive apprenticeship, a foundational pedagogy in the learning sciences, also draws attention to the sociology of a learning environment, including situated activity, communities of practice, meaningful participation, cooperation, and motivation (Collins et al., 1991). Collins et al. (1991) argue that these conditions shape whether learners are willing and able to engage in the difficult forms of cognitive construction that learning requires.

One condition Collins et al. argue for is situated activity: the learning of knowledge and skills in contexts similar to those where they will actually be used, giving learners opportunities to engage with meaningful tasks that emulate real-world practice. Such experiences provide contexts for exploration, error, uncertainty, and later reflection, using tools, skills, and strategies like those in authentic contexts. But these forms of learning are costly. They require time, patience, expertise, and environments where learners feel supported enough to expose incomplete thinking, make mistakes, disagree, ask for help, and revise their understanding. GenAI may help reduce costs by providing some necessary knowledge and guidance, but creating positive environments where learners feel safe taking intellectual risks largely

depends on a teacher's ability to curate an environment that promotes positive, interdependent relationships among learners: a community of learners (Rogoff, 1994; Brown & Campione, 1996).

Importantly, *the increased flexibility GenAI can provide in real time makes the teacher's role more, not less, consequential*. If scripting can occur dynamically, decisions previously embedded in the design of a learning environment or class activity increasingly become orchestration decisions made as learning unfolds. Teachers must determine not only what forms of support might be productive, but also when intervention is warranted, what kind of intervention is appropriate, how much support to provide, and when learners would benefit more from struggling, negotiating, or resolving problems themselves.

GenAI may expand the range of interventions that can be produced in the moment, but it does not resolve these pedagogical judgments. Instead, it creates a need for teachers to establish the goals, constraints, and principles that govern how and when AI-generated support is used. In this sense, GenAI shifts scripting from a relatively fixed support structure toward a more dynamic process of teacher orchestration in which support can be continually calibrated to the emerging needs of learners and groups. The improvisational decisions needed to prioritize learner-centered educational spaces are hard enough, without adding technologies that complicate the moment-by-moment decisions teachers must make (Amarasinghe et al., 2021; Sawyer, 2004).

Teachers can work with learners to decide when to prioritize efficiency, eliminating the need to treat scripting as an all-or-nothing design decision. Ideally, the classroom community could make these moment-by-moment decisions through ongoing discussion and reflection (Rogoff, 1994). In this way, learners and teachers may make mistakes in the moment during a session, but the class can discuss and unpack these errors to improve moment-by-moment decisions in the future (Lemke, 2000). These ongoing reflective discussions matter because what learners take from the classroom can shape how they navigate activities outside it (Barron, 2006), hopefully leading to more responsible GenAI use beyond the classroom.

For this reason, instructors and facilitators remain pivotal regardless of what technologies we introduce, but especially when GenAI is present. The teacher's role is not simply to provide information that a technological system can now generate. Teachers help create the larger learning ecology in which technology is used (Borge & Mercier, 2019; Cobb et al, 2003). Teachers must interpret what is happening across the classroom in real time and decide when to intervene and when to let learners struggle (Tissenbaum & Slotta, 2019). They select and orchestrate meaningful activities, establish norms for participation, cultivate belonging and trust, connect learners with one another, help communities work through problems, and create opportunities for collective reflection and problem-solving across pairs, teams, and the larger learning community.

This point is particularly important because preserving productive struggle does not require unnecessarily frustrating learning. Belonging, curiosity, shared purpose, and the satisfaction of solving meaningful problems with others can make learners more willing to tolerate the uncertainty and difficulty associated with deeper construction (Authors 2023). GenAI may reduce difficulty by providing

information, orchestrating team activity, supporting reflection, etc., but a learning community can give meaning to engaging with difficult problems and provide the emotional connection that makes these experiences rewarding and worth working through.

From this perspective, GenAI should be treated as a resource within a socially organized learning environment, not as a replacement for it. The long-term aim is not to create a frictionless relationship between an individual learner and an intelligent system. It is to cultivate learners who can think, learn, create, and solve meaningful problems with others while becoming increasingly capable of deciding when and how technological resources should support that work.

In our previous work, we knew the CREATE system alone was not sufficient to support the conditions for learning. Teachers were critical to creating a culture of learning where learners feel valued, safe to observe, explore, and participate in expert practice; Teachers also had to design activities that promoted intrinsic motivation, where learners want to engage in activities; finally, because learning is a nested activity, teachers also had to create opportunities for collective problem-solving outside of the system, between groups and at the level of the entire classroom community where they could encourage learners to discuss problems and strategies they have or could develop to prevent or reduce problems.

Conclusion

In this report, we reviewed the main tensions that helped develop the CSCL field over the past twenty years and developed current insights for educators and designers to integrate GenAI into collaborative learning contexts. We argued that integrating Generative AI into collaborative learning contexts requires a deliberate pedagogical shift from rigid task pre-structuring to supporting adaptive regulation and critical sensemaking. To do so in a way that supports the development of necessary underlying thinking processes, we must distinguish between focal and supporting learning processes; technology should not eliminate difficulty at the expense of meaningful knowledge construction. While GenAI can effectively streamline supporting procedural tasks, preserving space for exploratory dialogue, human judgment, and productive struggle remains essential for long-term competence. By applying a theoretically grounded framework to activity, information, and interaction design, educators and designers can leverage GenAI as a flexible resource. Doing so ensures that AI amplifies human agency, enriches collaborative discourse, and maintains the social and emotional richness that underpins true collective learning.

Educational design has always required navigating competing goals and trade-offs rather than identifying universally optimal forms of support (Collins, 1996), but these trade-offs become more critical as we introduce powerful technologies that can adaptively reduce cognitive complexity for learners without teacher input in ways that could produce long-term developmental detriment. With great power... Well, even though we did not create these LLM technologies, we still bear a responsibility to translate what we have learned as a field into practical knowledge that teachers, learners, and

educational policymakers can use to make informed decisions about how they design and use technology to support learning.

Declarations

Author Contribution

M.B. was responsible for conceptualization, developing the core theoretical framework, preparing the initial manuscript outline, and writing the original draft. T.S. contributed substantially through conceptual refinement, extensive review and revision, expansion of key sections, development of specific examples, and identification and integration of relevant literature. Both authors contributed to interpreting and refining the manuscript's central arguments, critically reviewed the manuscript for important intellectual content, and approved the final version.

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